



RESEARCH LETTER

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Key Points:

- A comprehensive analysis of U.S. dissection density with a novel method
- Spatial variation of dissection density depends on local geologic character and history
- Variance analysis based geographical detector method has great potential in geosciences research

Supporting Information:

- Figures S1–S10 and Table S1
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Spatial association between dissection density and environmental factors over the entire conterminous United States

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Abstract Previous studies of land dissection density (D) often find contradictory results regarding factors controlling its spatial variation. We hypothesize that the dominant controlling factors (and the interactions between them) vary from region to region due to differences in each region's local characteristics and geologic history. We test this hypothesis by applying a geographical detector method to eight physiographic divisions of the conterminous United States and identify the dominant factor(s) in each. The geographical detector method computes the power of determinant (q) that quantitatively measures the affinity between the factor considered and D . Results show that the factor (or factor combination) with the largest q value is different for physiographic regions with different characteristics and geologic histories. For example, lithology dominates in mountainous regions, curvature dominates in plains, and glaciation dominates in previously glaciated areas. The geographical detector method offers an objective framework for revealing factors controlling Earth surface processes.

1. Introduction

A bird's eye view of the land surface reveals its dissection by an intricate pattern of valleys. Moreover, this pattern exhibits significant spatial variability in its form and density. The density of valleys, a parameter that quantitatively describes the degree of land surface dissection by erosional processes, is defined as the total length of valleys per unit area. Note the distinction between the density of valleys, which is a geomorphic measure, and the closely related drainage density (the total length of streams per unit area [Horton, 1945]), which is a hydrologic measure and requires identification of channels. In this paper we will focus on the density of valleys because it is more readily calculated on the continental scale. Since the two measures are highly correlated on continental scale, we will make no distinction between the two and hereafter refer to them as the dissection density (D).

An understanding of what environmental factors control or influence the value of D and its spatial variation is one of the central themes in geomorphology and hydrology and is of considerable conceptual [Luoto, 2007] and practical interests as the question is intimately related to the problem of assessing the risk of damage and degradation of landscape and the designing of measures to reduce such damage. However, it remains an unsolved problem despite numerous previous attempts to address it.

Previous studies into the factors controlling the value of D have resulted in a large body of literature. As Schumm and Lichty [1965] eloquently pointed out, the cause and effect in geomorphology depends on the span of time involved and the size of the geomorphic system under consideration. Since our primary concern here is the continental-scale spatial pattern of D that is most likely established over geologic timescale, we will focus primarily on those factors most relevant to the large spatial and long temporal scales under consideration. The following is a brief summary of factors identified as having a significant influence on the value of D .

Climate. Various measures of precipitation rate have been used as proxies of climate in studies aimed at establishing a relation between D and climate. The first investigations [Melton, 1957] revealed an inverse relation between D and precipitation, but subsequent investigations [Chorley, 1957; Gregory and Gardiner, 1975; Gregory, 1976] pointed to a positive correlation between D and precipitation. Channel initiation and landscape evolution models [Montgomery and Dietrich, 1989; Tucker and Bras, 1998] also predict a positive correlation between D and precipitation.

Slope and Relief. Slope gradient and relative relief have been identified as the main morphological factors controlling dissection density. Multiple investigations [Schumm, 1965; Strahler, 1964] found a positive relation between D and relief. However, theoretical calculations [Howard, 1977] indicate that the relationship between relief and D should change from positive to negative with increasing relief as a consequence of different channel initiation processes. Indeed, such negative relation has been found in deep valleys located in steep mountains in areas with high humidity [Oguchi, 1997].

Lithology. Differences in the values of D between regions of similar climate have been related to bedrock geology [Strahler, 1964; Wilson, 1971; Day, 1980]. Greater drainage densities were generally associated with more impermeable rocks [Gardiner, 1995]. Bedrock erodibility also is proposed as a predictor of D [Tucker and Slingerland, 1996].

Soil properties. Soil parameters affect land surface resistance to erosion by surface flow and their variability produces different values of D [Dietrich et al., 1992; Rinaldo et al., 1995; Tucker and Slingerland, 1997]. Dissection density is generally inversely related to the hydraulic conductivity of the underlying soil [Montgomery and Dietrich, 1989].

Vegetation cover. The importance of vegetation cover as a limiting factor for the value of D has been pointed out in previous studies [e.g., Melton, 1958; Moglen et al., 1998]. Vegetation cover alters soil critical shear stress and, thus, influences dissection threshold [Tucker and Slingerland, 1997; Prosser and Dietrich, 1995]. The complexities inherent in biogeomorphic systems have been modeled by coupling climatic, ecological, and geomorphological processes, which showed both positive and negative correlation between D and vegetation depending on climate regimes [Collins et al., 2004; Istanbuloglu and Bras, 2005; Collins and Bras, 2010]. Smith et al. [2013] examined the relationship between D and vegetation in the context of global warming on decadal timescale.

The aforementioned factors are expected to nonlinearly interact with each other in influencing the value of D . Abrahams [1984] observed that several climatic factors simultaneously affect D in a complex way. The interplay of different controlling factors on the value of D has been found in both field observations [Melton, 1957; Strahler, 1964; Toy, 1977] and in landscape evolution models [Rinaldo et al., 1995; Tucker and Bras, 1998; Tucker et al., 1997; Prosser and Dietrich, 1995; Moglen et al., 1998; Collins and Bras, 2010].

Most of the previous studies were at local scales and these studies lacked an analytical framework designed especially for objectively comparing multiple factors over a regional or continental scale. We hypothesize that the sometimes contradictory results from previous studies regarding controlling factors of D are simply because factors controlling spatial distribution of D vary by region (i.e., conclusion from one region cannot be generalized and applied to other regions). We further hypothesize that the dominant factor (or interaction of factors) controlling D of an area would likely be consistent with and reflect that area's geologic history. To the best of our knowledge, these hypotheses have not been tested rigorously. Here we test them by applying a geographical detector method [Wang et al., 2010] to physiographic divisions (hereafter loosely referred to as regions unless a distinction is needed) of the conterminous United States [Fenneman, 1928, 1946, <http://water.usgs.gov/GIS/metadata/usgswrd/XML/physio.xml>; Hunt, 1967] and to identify the dominant factors and combination of factors in each region quantitatively. The difference in dominant factors by region and their relationship with the region's geologic history will then be discussed and analyzed qualitatively.

A physiographic region is a naturally occurring region on Earth having certain common (homogeneous) landform characteristics that make it different from neighboring regions [Fenneman, 1928; Hunt, 1967]. The boundaries of such regions are often determined by the geologic structures, the tectonic and erosional processes involved, and stage of the processes, i.e., distinguished by their physiographic histories [Fenneman, 1928]. Thus, physiographic regions provide natural units to test our hypotheses. The conterminous US is divided into eight physiographic divisions. Each division is further divided into provinces and provinces sections [Fenneman, 1928; Hunt, 1967], but we will focus primarily at the division level. Table S1 in the supporting information is a brief summary of the geologic characteristics and histories of each region.

2. Method

The geographical detector method [Wang et al., 2010; Hu et al., 2011] is a spatial variance analysis method developed in the context of medical geography to assess the associations between a health outcome, such as disease prevalence and mortality, and feasible risk factors, such as pollution in environment and social

economic status [Hu et al., 2011; Li et al., 2013; Cao et al., 2013]. The geographical detector method is especially good at analyzing categorical data. Details about geographical detector can be found in the original paper [Wang et al., 2010]; here we review the method briefly within our present context.

Let X be a layer of data representing an environmental factor (e.g., lithology or slope) that we want to test for being a factor in spatial distribution of D (see Figure S1). Because the geographical detector works with categorical variables, X must either be already a categorical layer (e.g., lithology) or needs to be categorized (e.g., slope angle can be categorized to into three categories: gentle, moderate, and steep). If X is a continuous raster, it is segmented into zones (clumps of single category). There are as many zones of clumps as there are categories of X . For example, if X is the slope categorized into three categories, there are three categorical zones of slope in the study area. Overlaying D and X layers subdivides D according to the zones of X (see Figures S1a and S1b).

The geographical detector method is based on analysis of the variance of D by the zones of each factor under consideration. The key underlying assumption is the following: if the factor X is associated with D , then D would exhibit a spatial distribution similar to that of X . In the perfect case in which factor X completely explains pattern of D , the value of D would be uniform across each zone of X and spatial variance of D within all zones would be 0. In a realistic case, the degree of spatial correspondence between layers X and D is measured by the power of determinant (q) for a factor X which is defined as

$$q_X = 1 - \frac{1}{N\sigma^2} \sum_{z=1}^L N_z \sigma_z^2 \tag{1}$$

where σ_z^2 is the variance of D within zone z of the environmental factor X , N_z is number of sample units in zone z , σ^2 is global variance of D in the entire study area, N is the number of total samples in the entire study area, and L is the number of zones (categories) of the factor X . The standard definition of σ_z^2 and σ^2 apply here

$$\sigma_z^2 = \frac{1}{N_z - 1} \sum_{i=1}^{N_z} (D_{z,i} - \bar{D}_z)^2 \tag{2}$$

where $D_{z,i}$ is the value of i th sample unit of D in zone z and \bar{D}_z is the mean of D in zone z .

$$\sigma^2 = \frac{1}{N - 1} \sum_{j=1}^N (D_j - \bar{D})^2 \tag{3}$$

where D_j is the value of the j th sample unit from the entire study area and \bar{D} is the global mean of D over the entire study area.

Note that the second term in equation (1) is a ratio of the weighted sum of local variance (weighted by the number of samples in each zone) to the global variance. If factor X completely controls the spatial distribution of D , local variance is 0 and $q_X = 1$ (assuming $\sigma^2 \neq 0$). If factor X is completely unrelated to the spatial distribution of D , the weighted sum of local variance is the same as the global variance and $q_X = 0$. In general, $q_X \in [0, 1]$ reflects the proportion of spatial variation of D explained by the factor X . Higher values of q_X indicate higher affinity of X and D . Note that this method assesses degree of affinity or spatial association and not specifically a degree of causal relation between X and D . The power of determinant (q_X) is termed the “factor detector” [Wang et al., 2010] and addresses the question “which environmental factor is more strongly associated with the spatial distribution of D and thus could be a controlling factor?”

Interaction between two different factors X and Y is assessed by comparing values of $q_{X \cap Y}$ with values of q_X and q_Y , where $q_{X \cap Y}$ indicates the power of determinant for a new factor created by overlaying factors X and Y (see Figure S1). This makes it possible to calculate so-called “interaction detector” [Wang et al., 2010]. If $q_{X \cap Y} > q_X$ or $q_{X \cap Y} > q_Y$, the variables enhance each other; if $q_{X \cap Y} > q_X$ and $q_{X \cap Y} > q_Y$, the variables bienhance each other; if $q_{X \cap Y} > q_X + q_Y$, the variables nonlinearly enhance each other. If the unequal sign is “<” in previous situations, the two variables respectively weaken, biweaken, or nonlinearly weaken each other. If $q_{X \cap Y} = q_X + q_Y$, then they are independent of each other. The free software for conducting geographical detector analysis can be downloaded from <http://www.sssampling.org/Excel-Geodetector/>.

3. Data

3.1. Dissection Density (D) Data

High-resolution, consistent, and artifact-free dissection density data for the entire U.S. is the key input variable. An attempt to calculate D using the National Hydrography Dataset (NHD), a data set of hydrographic

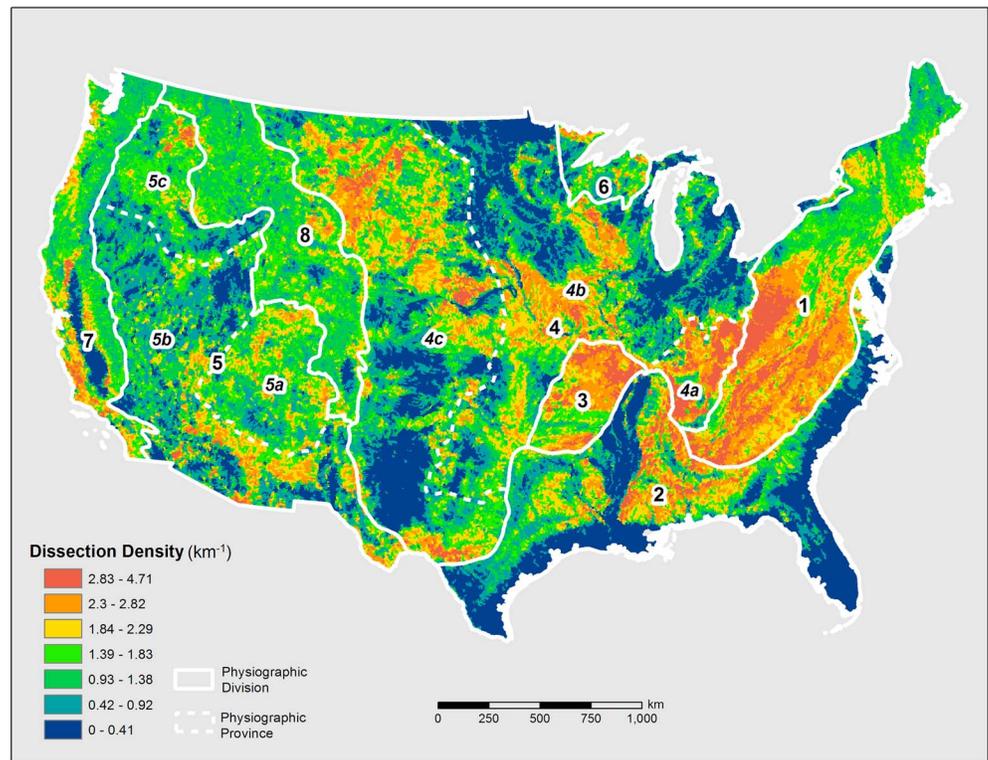


Figure 1. Map of dissection density (D) derived using the geomorphon method (resolution 4 km/cell). White boundaries delineate the eight physiographic divisions (1 = Appalachian Highlands, 2 = Atlantic Plain, 3 = Interior Highlands, 4 = Interior Plains (4a = Interior Low Plateau, 4b = Central Lowlands, and 4c = Great Plains), 5 = Intermontane Plateaus (5a = Colorado Plateau, 5b = Basin and Range, 5c = Columbia Plateau), 6 = Laurentian Upland, 7 = Pacific Mountain System, and 8 = Rocky Mountain System). For clarity, watershed boundaries are not shown.

features including streams, has failed to yield an artifact-free map of dissection density. This is because both, medium- and high-resolution, versions of NHD are compilations of locally gathered data sets and lack consistency between different quadrangles needed to form a single, country-wide map of D .

Instead, we have used the geomorphons method [Jasiewicz and Stepinski, 2013] to derive a consistent, artifact-free, country-wide map of D using digital elevation model (DEM) data. A complete description of the geomorphons method is beyond the scope of this paper, but a brief illustration of the concept is provided in Figure S2. The geomorphons method is implemented as an add-on module to GRASS GIS software (<https://grass.osgeo.org/grass70/manuals/addons/r.geomorphon.html>, source code is available at http://sil.uc.edu/cms/data/uploads/software_data/r.geom.zip); for small DEMs it is also available as an online application (<http://sil.uc.edu/geom/app>). We choose the U.S. Geological Survey 1" resolution National Elevation Dataset (NED) because this resolution offers a good balance between the level of details, the practicality of calculation over the entire conterminous U.S., and the absolute vertical root-mean-square error of 2.44 m [Gesch et al., 2014], which is sufficient for the continental-scale study. The data were then reprojected to the National Atlas Equal Area Projection, resulting in a data set of $168,000 \times 104,000$ cells, each with 30 m resolution. In the next step, we classify NED cells into 10 common landform elements using the geomorphons method with the following values of parameters: a maximum search radius equal to 50 cells and a flatness threshold equal to 1° [Jasiewicz and Stepinski, 2013]. The resulting geomorphon map of the entire conterminous U.S. can be explored using the GeoWeb application DataEye (<http://sil.uc.edu/>). Next we identify valleys with 2 (out of 10) geomorphon-mapped landform elements: valleys and pits. As our goal was to depict the land surface incisions from well-defined geomorphological forms, we excluded less distinct slope drainage elements such as hollows. As a result we obtained a cell-based map of valleys made of lines of different thicknesses, which were subsequently thinned to 1 cell width skeletons using GRASS GIS *r.thin* module [Jang and Chin, 1990]. To calculate the lengths of the thinned lines, we assigned to every cell a length as follows: the starting length of a cell was 0 m; in the 8-cell neighborhood, for every edge-contacted cell we added 15 m, for every corner contacted cell we added 21.21 m. D is calculated at a watershed

Table 1. Factors Selected for Analysis^a

| Category | Factor | Factor Code | Source/URL |
|--------------------------|----------------------------------|-------------|---|
| Geology or soil property | Glaciation | Glaci | http://esp.cr.usgs.gov/info/gmna/ |
| | Lithology | Litho | http://rmgsc.cr.usgs.gov/outgoing/ecosystems/USdata <i>Gleeson et al.</i> [2014] |
| | Permeability | logk | |
| | Porosity | poro | STATSGO2 database |
| Climate | Precipitation | precip | http://www.prism.oregonstate.edu/ , 4 km resolution |
| Topography or terrain | Elevation | elev | ETOPO1 DEM resampled to 4 km resolution |
| | Aspect | asp | Derived from DEM, 4 km resolution |
| | Slope | slp | Derived from DEM, 4 km resolution |
| | Difference in elevation (relief) | difelev | Derived from DEM, 4 km resolution |
| | Distance to erosional base | distb | Derived from DEM, 4 km resolution |
| | Elevation to erosional base | elevb | Derived from DEM, 4 km resolution |
| | Planar Curvature | planc | Derived from DEM, 4 km resolution |
| | Tangential Curvature | tanc | Derived from DEM, 4 km resolution |

^aSee supporting information (Figures S4–11) for spatial distribution of selected factors.

level (as the total length of skeleton valleys falling within a watershed divided by the area of the watershed) using the 12 digit hydrologic unit boundaries [*U.S. Geological Survey and U.S. Department of Agriculture, Natural Resources Conservation Service, 2013*], which is the finest-resolution unit available for this data set. The entire procedure, starting from a DEM and ending with map of *D*, is illustrated in Figure S3. The overall spatial pattern of *D* across the entire conterminous U.S. is shown in Figure 1; it closely resembles the pattern on a corresponding map computed using the NHD streams, but it is spatially consistent and artifact free. The traditional definition of drainage density makes most sense for erosional landscapes. Our method is more general and works for all landscapes, erosional, or depositional.

3.2. Potential Controlling Factors Data

We have collected (from various sources) a set of 13 layers of environmental variables (factors) that are available in the public domain and may conceivably correlate with *D*. The factors can be roughly grouped into three categories and their brief descriptions and sources are summarized in Table 1. We did not include factors that are deemed more important at short timescales such as land cover and vegetation in our analysis because our focus here is the spatial distribution of dissection density over large spatial scale (the entire continental U.S.), which is most likely established over long geologic time [*Schumm and Lichty, 1965*].

To be consistent with the basic watershed units used to derive *D*, we calculated the values for each factor by watershed using zonal mean (for real value data) and zonal majority (for categorical data), i.e., mean/majority of cells within each watershed. There were a total of 85,349 hydrologic units (average size ~100 km²), with each containing the value of *D* and values of 13 selected factors (see Figures S4–S11 for selected examples). These were then divided into physiographic regions. Factors consisting of real-valued data in each region were discretized into six categories (ordinal levels) according to quantile method [*Cao et al., 2013*] to compute the *q* value for that region (see Figure S6b for an example).

4. Results and Interpretation

Table 2 shows the factor with the largest *q* (i.e., the dominant factor) and interaction between pair of factors with largest *q* (i.e., the dominant interaction) for each physiographic region (see supporting data file Data Set S1 and Data Set S2 for *q* values for all factors and interactions). We use the word “dominant” hereafter in a relative sense to indicate that a factor or interaction has the largest *q* value comparing with the *q* of other factors or interactions. Table 2 indicates that different physiographic regions generally have different dominant factors and factor interactions. Comparing Tables S1 and 2 shows that each region’s dominant factor and dominant interaction of factors are generally consistent with the region’s characteristics and geologic history. For example, lithology (*q* = 0.49) and glaciation (*q* = 0.48) are the most important single

Table 2. Factor or Factor Interaction With Maximum q Value

| Physiographic Division/Province Name (#) | Dominant Factor | q | Dominant Interaction | q |
|--|-----------------|------|---------------------------------------|------|
| Appalachian Highlands (1) | litho | 0.49 | litho \cap elev | 0.58 |
| Atlantic Plain (2) | planc | 0.46 | elev \cap precip ^a | 0.62 |
| Interior Highlands (3) | logk | 0.31 | logk \cap precip | 0.47 |
| Interior Plains (4) | planc/tanc | 0.29 | litho \cap planc/litho \cap tanc | 0.40 |
| Interior Low Plateau (4a) | litho | 0.21 | logk \cap litho/logk \cap difelev | 0.34 |
| Central Lowlands (4b) | glaci | 0.36 | glaci \cap planc/glaci \cap tanc | 0.52 |
| Great Plains (4c) | planc | 0.24 | logk \cap litho/logk \cap tanc | 0.34 |
| Intermontane Plateaus (5) | litho | 0.31 | litho \cap slp | 0.37 |
| Colorado Plateau (5a) | litho | 0.13 | litho \cap planc | 0.20 |
| Basin and range (5b) | litho | 0.35 | Litho \cap slp/litho \cap tanc | 0.41 |
| Columbia Plateau (5c) | litho | 0.33 | litho \cap precip | 0.46 |
| Laurentian Upland (6) | litho | 0.23 | litho \cap tanc | 0.32 |
| Pacific Mountain System(7) | elev | 0.28 | elev \cap precip ^a | 0.43 |
| Rocky Mountain System (8) | litho | 0.10 | litho \cap tanc/litho \cap slp | 0.18 |

^aIndicates nonlinear enhancement; the rest of interactions are bienhancing/indicates the two factors or factor combinations with almost equal q value (see Figure 1 for physiographic division and province location and Table 1 for full factor name. See supporting information Figures S12 and S13 and Data Sets S1 and S2 for full results.)

factors associated with D for Appalachian Highlands (region 1). The glaciation of its northern part since Pleistocene left glacial deposits, which resulted in relatively low D in comparison with the southern part of the region, where long term erosion of exposed bedrock resulted in high D (see Figure S4 and S5). Even though elevation and relief alone each has low q value, but they are important in this highland area because they interact with lithology to explain over 58% of the variations in D (see Figure S6).

In Atlantic Plain (region 2), the dominant factor is planar curvature ($q = 0.46$, Figure S7), which is followed closely by tangential curvature and slope (both $q = 0.44$, Figures S8 and S9). We interpret the high association of D with curvatures and slope as follows: in the generally low relief and flat coastal plains, where there is no other strong factors affecting erosional potential of surface water flow, the slight increase in curvatures and slope could make a noticeable difference in the acceleration and convergence of flow across the land surface, creating stronger erosion and incision at those locations. Alternatively, this high association may simply reflect that valley and pit types of geomorphon, the curvatures, and slope capture similar characteristics of the terrain. The interaction of precipitation and elevation and that between precipitation and slope can account for 62% and 59%, respectively, of the spatial variation in D , consistent with this region's generally humid climate (see Figure S10).

The dominant factor for Interior Highlands (region 3) is permeability ($\log k$, Figure S11) and the dominant interaction is between permeability and precipitation. The high rock permeability generally associated with carbonate would promote infiltration, leading to less surface runoff, less surface dissection, and low D . The zonal mean value of D for the highest permeability zone in this region is indeed the smallest, although the trend in other zones is not always consistent, which calls for further future study (see Figure S12). The higher precipitation values along either side of the southern valley of this region, perhaps related to orographic effect, interacted with permeability to produce the high q value.

The Interior Plains (region 4), again being mostly a flat, low-relief area (except the western edge), for reasons similar to region 2, has planar and tangential curvatures as the dominant factors (both $q = 0.29$) and interaction between lithology and both curvatures being dominant (both $q = 0.40$). Since the Interior Plains is large, we also computed the q value for its constituent provinces (see regions 4a–c in Table 2), which again reveals dominant factors consistent with local characteristics and histories. The dominant factor for Interior Low Plateau (region 4a) is lithology ($q = 0.21$) and dominant interaction is between lithology and permeability and between permeability and relief (difelev) (both $q = 0.34$). The contrast between the limestone in the south and the colluvium material in the north of this region (see Figure S4) and the associated difference in permeability likely controlled the spatial distribution of D . Zonal mean of D by permeability zones shows consistent decreasing trend with increasing permeability, as expected (see Figure S13). The majority of Central Lowland (region 4b) was glaciated during last glaciation and earlier glaciation (see Figure S5). The northern area (covered by ice during last glaciation) has relatively low D , in contrast to the relatively high

D in the area glaciated earlier, which were affected by intensive erosion during last (more recent) glacial cycle and the geographical detector identified the dominant factor as glaciation ($q = 0.36$), consistent with expectation. The dominant interaction is between glaciation and both curvatures (both $q = 0.52$), consistent with important role of curvatures in converging and accelerating water in flat, low-relief area. The dominant factor for Great Plains (region 4c), with flat and low relief, composed of sediments eroded from Rocky Mountains, is planar curvature. This is consistent with other regions that have flat and low relief (e.g., regions 2 and region 4 as a whole) also have curvature as dominant factor. The high permeability associated with mountain front colluvial and eolian sediments contributed to the low D values there and thus dominant interactions are between permeability and lithology and between permeability and tangential curvature (both $q = 0.34$).

The Intermontane Plateaus (region 5), Laurentian Upland (region 6), and Rocky Mountain Systems (region 8) are all characterized by exposed bedrock formed by tectonic events. Lithology is consistently identified as the dominant factor for all of them and the interaction between lithology and slope and/or curvatures enhance their q values. Lithology is also the dominant factor for each province of region 5, although the dominant interactions are between lithology and different factors (planar curvature for Colorado Plateau, slope and tangential curvature for Basin and Range, and precipitation for Columbian Plateau). These dominant interactions again reflect their local conditions. For example, on Colorado Plateau with relatively low relief, flow acceleration, and deceleration (characterized by planar curvature) is more important than other factors and in Basin and Range with alternating up and down topography, the role of gravity and flow convergence (characterized by slope and tangential curvature) is more important than other factors.

In Pacific Mountain Systems (region 7), elevation is identified as the dominant factor ($q = 0.28$), followed by lithology ($q = 0.24$), and the dominant interaction is between elevation and precipitation ($q = 0.43$), followed by that between elevation and lithology ($q = 0.42$). This is consistent with the region's contrast of elevation between rugged mountains and intermountain troughs and also reflects the importance of orographic effect on precipitation in this area (see Figures S6 and S10).

In summary, the geographic detector method identified different dominant factors (and factor interactions) for different physiographic divisions and the difference in dominant factors (and interactions) appear to reflect the differences in local characteristics and geologic histories for all of physiographic regions considered.

5. Discussion and Conclusion

The purpose of this paper is to test the hypotheses that factors potentially controlling spatial distribution of D vary by region and the dominant factors reflect the region's local geologic character and history. Although this hypothesis sounds simple and straightforward, it has not been tested rigorously in the literature before. This study takes advantage of the ready availability of various potential factors data in digital form, the geomorphon method which allows us to derive consistent D map over the entire conterminous U.S., and the novel computational framework of geographical detector which enables us to quantify and compare the spatial association between D and various factors and interaction of factors in different physiographic regions.

We stress that our method itself finds spatial statistical association and not causations. For historical reasons, we frequently refer to variables with high levels of association with D as "factors," but no causality is implied. However, just like in medical geography studies, finding these high association factors is the first step toward identifying causality with further analysis. Our qualitative assessment of these dominant factors by comparing them with the local geologic characters and histories does show general consistency throughout the eight physiographic regions considered.

In regions with exposed bedrock (e.g., Appalachian Highlands, Intermontane Plateaus, Laurentian Upland, and Rocky Mountain System), lithology is usually the dominant factor. In addition, it is interesting to note that in the regions that are more tectonically active in recent geologic past, the q values are generally smaller (e.g., Rocky Mountain System, $q = 0.10$) than those in regions that are ancient and less tectonically active (e.g., Appalachian Highlands, $q = 0.48$). This may be because in tectonically active regions the dominance of lithology on the development of drainage systems can be easily disrupted by tectonic activities, whereas in tectonically stable environment lithology has more time to exert control on the advanced development of drainage systems. For flat, low-relief areas (e.g., Atlantic Plains and Interior Plains), planar or tangential curvatures, which controls the acceleration and convergence of surface water

flow across land surface, are usually the dominant factors. In regions that were glaciated (e.g., Central Lowlands and northern Appalachian Highlands), glaciation is the dominant (or second most dominant) factor. In limestone area (e.g., Interior Highlands), permeability is the dominant factor, consistent with the fact that solubility of limestone can create high permeability, leading to less surface runoff and low D . We have also demonstrated that two factors can interact with each other to increase their combined affinity with the D , i.e., to increase the percentage of variance explained and in some cases nonlinearly (i.e., higher than the sum of individual qs , reaching 62% in one case). The top interactions between factors are also consistent with and reflect the local regions' geologic character and history.

In conclusion, our results based on data and analysis over the entire conterminous U.S. demonstrate that different regions do have different dominant factors and interaction between factors and these differences are generally consistent with the differences in each region's local characteristics and geologic history (for which, at present, we cannot account quantitatively, but they do make qualitative sense). These consistencies throughout physiographic divisions/provinces considered indicate that they are unlikely to be by chance and thus provide strong support to our hypotheses. Our results also suggest that the geographical detector offers a quantitative and objective analytical framework that could be used to find potential controlling factors of other geoscience phenomena for focused further analysis.

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References

- Abrahams, A. D. (1984), Channel networks: A geomorphological perspective, *Water Resour. Res.*, *20*, 161–168.
- Cao, F., Y. Ge, and J. F. Wang (2013), Optimal discretization for geographical detectors-based risk assessment, *GISci. Remote Sens.*, *50*(1), 78–92.
- Chorley, G. (1957), Climate and morphometry, *J. Geol.*, *65*, 628–638.
- Collins, D. B. G., and R. L. Bras (2010), Climatic and ecological controls of equilibrium drainage density, relief, and channel concavity in dry lands, *Water Resour. Res.*, *46*, W04508, doi:10.1029/2009WR008615.
- Collins, D. B. G., R. L. Bras, and G. E. Tucker (2004), Modeling the effects of vegetation-erosion coupling on landscape evolution, *J. Geophys. Res.*, *109*, F03004, doi:10.1029/2003JF000028.
- Day, D. G. (1980), Lithologic controls of drainage density: A study of six small rural catchments in New England, N.S.W., *Catena*, *7*, 339–351.
- Dietrich, W. E., C. J. Wilson, D. R. Montgomery, J. McKean, and R. Bauer (1992), Erosion thresholds and land surface morphology, *Geology*, *20*, 675–679.
- Fenneman, N. M. (1928), Physiographic Divisions of the United States, *Ann. Assoc. Am. Geogr.*, *18*(4), 261–353.
- Fenneman, N. M. (1946), Physical divisions of the United States: Washington, D.C., U.S. Geol. Surv. special map, scale 1:7,000,000.
- Gardiner, V. (1995), Channel networks: Progress in the study of spatial and temporal variations of drainage density, in *Changing River Channels*, edited by A. Gurnell and G. E. Petts, pp. 65–85, Wiley, New York.
- Gesch, D. B., M. J. Oimoen, and G. A. Evans (2014), Accuracy assessment of the U.S. Geological Survey National Elevation Dataset, and comparison with other large-area elevation datasets—SRTM and ASTER, *U.S. Geol. Surv. Open File Rep.*, *2014–1008*, 10 p., doi:10.3133/ofr20141008.
- Gleeson, T., N. Moosdorf, J. Hartmann, and L. P. H. van Beek (2014), A glimpse beneath Earth's surface: Global HYdrogeology MaPs (GLHYMPS) of permeability and porosity, *Geophys. Res. Lett.*, *41*, 3891–3898, doi:10.1002/2014GL059856.
- Gregory, K. J. (1976), Drainage networks and climate, in *Geomorphology and Climate*, edited by E. Derbyshire, pp. 289–315, Wiley, Chichester, U. K.
- Gregory, K. J., and V. Gardiner (1975), Drainage density and climate, *Z. Geomorphol.*, *19*, 287–298.
- Horton, R. E. (1945), Erosional development of streams and their drainage basins: Hydrophysical approach to quantitative morphology, *Bull. Geol. Soc. Am.*, *56*, 275–370.
- Howard, A. D. (1977), Badland morphology and evolution: Interpretation using a simulation model, *Earth Surf. Processes Landforms*, *22*, 211–227.
- Hu, Y., J. F. Wang, X. H. Li, and J. Zhu (2011), Geographical detectors-based risk assessment of the under-five mortality in the 2008 Wenchuan earthquake, China, *PLoS One*, *6*(6), e21427.
- Hunt, C. B. (1967), *Physiography of the United States*, p. 480, Freeman and Company, San Francisco, Calif.
- Istanbulluoglu, E., and R. L. Bras (2005), Vegetation-modulated landscape evolution: Effects of vegetation on landscape processes, drainage density, and topography, *J. Geophys. Res.*, *110*, F02012, doi:10.1029/2004JF000249.
- Jang, B. K., and R. T. Chin (1990), Analysis of thinning algorithms using mathematical morphology, *Pattern Anal. Mach. Intell., IEEE Trans.*, *12*(6), 541–551.
- Jasiewicz, J., and T. F. Stepinski (2013), Geomorphons—A pattern recognition approach to classification and mapping of landforms, *Geomorphology*, *182*, 147–156.
- Li, X. W., Y. F. Xie, J. F. Wang, G. Christakos, J. Si, and H. Zhao (2013), Influence of planting patterns on fluoroquinolone residues in the soil of an intensive vegetable cultivation area in north China, *Sci. Total Environ.*, *458–460*, 63–69.
- Luoto, M. (2007), New insights into factors controlling drainage density in subarctic landscapes, *Arct. Antarct. Alp. Res.*, *39*(1), 117–126.
- Melton, M. A. (1957), An analysis of the relations among elements of climate, surface properties and geomorphology, Dep. Geol., Columbia Univ. Tech. Rep. 11, Proj. NR 389–042, O. of Nav. Res., New York.
- Melton, M. A. (1958), Correlation structure of morphometric properties of drainage systems and their controlling agents, *J. Geol.*, *66*, 442–460.
- Moglen, G. E., E. A. B. Eltahir, and R. L. Bras (1998), On the sensitivity of drainage density to climate change, *Water Resour. Res.*, *34*, 855–862.
- Montgomery, D. R., and W. E. Dietrich (1989), Source areas, drainage density, and channel initiation, *Water Resour. Res.*, *25*, 1907–1918.
- Oguchi, T. (1997), Drainage density and relative relief in humid steep mountains with frequent slope failure, *Earth Surf. Processes Landforms*, *22*, 107–120.
- Prosser, I. P., and W. E. Dietrich (1995), Field experiments on erosion by overland flow and their implication for a digital terrain model of channel initiation, *Water Resour. Res.*, *31*, 2867–2876.

- Rinaldo, A., W. E. Dietrich, R. Rigon, G. K. Vogel, and I. Rodriguez- Iturbe (1995), Geomorphological signatures of varying climate, *Nature*, 374, 632–634.
- Schumm, S. A. (1965), Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey, *Geol. Soc. Am. Bull.*, 67, 597–646.
- Schumm, S. A., and R. W. Lichty (1965), Time, space, and causality in geomorphology, *Am. J. Sci.*, 263, 110–119.
- Smith, V. B., C. H. David, M. B. Cardenas, and Z.-L. Yang (2013), Climate, river network, and vegetation cover relationships across a climate gradient and their potential for predicting effects of decadal-scale climate change, *J. Hydrol.*, 488, 101–109, doi:10.1016/j.jhydrol.2013.02.050.
- Strahler, A. N. (1964), Quantitative geomorphology of drainage basins and channel networks, in *Handbook of Applied Hydrology*, edited by V. T. Chow, pp. 4.39–4.76, McGraw-Hill, New York.
- Toy, T. J. (1977), Hillslope form and climate, *Geol. Soc. Am. Bull.*, 88, 16–22.
- Tucker, G. E., and R. L. Bras (1998), Hillslope processes, drainage density, and landscape morphology, *Water Resour. Res.*, 34, 2751–2764.
- Tucker, G. E., and R. L. Slingerland (1996), Predicting sediment flux from fold and thrust belts, *Basin Res.*, 8, 329–349.
- Tucker, G. E., and R. L. Slingerland (1997), Drainage basin responses to climate change, *Water Resour. Res.*, 33, 2031–2047.
- Tucker, G. E., N. M. Gasparini, S. T. Lancaster, and R. L. Bras (1997), An integrated hillslope and channel evolution model as an investigation and prediction tool, Tech. Rep. prepared for U.S. Army Corps of Engineers Construction Engineering Research Laboratories.
- U.S. Geological Survey and U.S. Department of Agriculture, Natural Resources Conservation Service (2013), Federal standards and procedures for the National Watershed Boundary Dataset (WBD) (4 ed.): U.S. Geological Survey techniques and methods 11–A3, 63 p. [Available on the World Wide Web at <http://pubs.usgs.gov/tm/tm11a3/>.]
- Wang, J. F., X. H. Li, G. Christakos, Y. L. Liao, T. Zhang, X. Gu, and Z. Y. Zheng (2010), Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China, *Int. J. Geogr. Inf. Sci.*, 24(1), 107–127.
- Wilson, L. (1971), Drainage density, length ratios, and lithology in a glaciated area of southern Connecticut, *Geol. Soc. Am. Bull.*, 82, 2955–2956.